Hospital Pairings and Cost Savings from Consolidation

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Abstract

In this paper, we use nonparametric estimation techniques to examine the potential and actual cost savings from a merger. In addition, merger types are categorized according to the ownership status, teaching status, hospital size and caseload severity of the merging hospitals. These merger types are investigated to determine the types of hospitals that tend to merge with each other and to analyze how differing merger types influence the cost savings from a merger. Our findings suggest that mergers have the potential to save costs, but these cost savings are not realized; costs are higher post-merger than pre-merger. Mergers between teaching and nonteaching hospitals, and hospitals with similar caseloads have the potential to improve cost savings, but the output mix is altered after the merger in such a way that any possible cost savings are eliminated. However, mergers between two large hospitals tend to decrease both potential and actual cost savings.

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1 Introduction

The last decade has seen a tremendous increase in the number of hospital mergers and acquisitions. Economic theory suggests that mergers and acquisitions occur in order to exploit economies of scale or market power and increase profitability. Indeed, structural changes in the health care industry such as implementation of the Prospecitive Payment System for Medicare reimbursements and the dominance of managed care plans and health maintenance organizations suggest that economic pressures faced by hospitals have served as a catalyst for these consolidations. Previous studies such as Sinay (1998) and Harrison (2002) support this theory, finding that hospitals facing increasing returns to scale, and hospitals with inefficient utilization of facilities, and lower market power are more likely to merge. The question of whether hospitals can capitalize on the potential economic advantages of a merger in order to improve their economic viability remains, however. This paper investigates this question by analyzing costs for hospitals before and after consolidation. In addition, the paper examines whether differing characteristics between merging hospitals affect the cost effectiveness of the merger or acquistion.

A few papers have studied the economic gains from consolidation. Alexander *et al.* (1996) investigate whether mergers improve economic efficiency at the merging hospitals. Without running formal regressions, they compare the pre-merger mean and the rate of change of average number of beds, adjusted admissions, occupancy rates, total expenses per adjusted admission, total number of staff, and total number of nurses to the post-merger values. They find that mergers provide short-term improvements in operating efficiency (occupancy rate, total expenses per adjusted admission), but not in the scale of operations (beds, admissions) or staffing practices (number of staff and number of nurses).

Connor *et. al* (1998) specifically study whether costs improve for merging hospitals relative to non-merging hospitals. They assess whether a merger significantly affects the change in average costs pre- versus post-merger while controlling for individual hospital characteristics such as changes in admissions, length of stay, outpatient visits, demographics of the patients, regional location, and population and per capita income in the area,. Their results show that cost inflation is approximately 5% lower for merging hospitals than for non-merging hospitals. Their study, however, fails to correct for the endogeneity of the dummy variable indicating whether a merger occurred. Merging hospitals may inherently have higher costs than their non-merging counterparts. These hospitals face downward pressure to reduce costs, and might have reduced costs even without a merger. In addition, they use average costs as their dependent variable. As discussed in Koop and Carey (1994), other modelling techniques derived from economic theory of cost minimization, such as the translog cost function, are generally more preferred. Nonetheless, their paper lays the groundwork for additional research into the cost savings from mergers.

Hospitals differ greatly in terms of ownership status, teaching status, hospital size, and severity of the patients served at the hospital. Thus, when two hospitals merge, they may differ in one or more of these characteristics. In this paper, we define a merger type to be a merger classified based on differences in characteristics between the merging hospitals. For example, a merger between two nonprofits is a different merger type than a merger between two for-profits, or between a nonprofit and a for-profit.

Controlling for such differences may be quite important when investigating cost savings from consolidation. Several studies suggest nonprofit hospitals have different objective functions than profit maximization (Newhouse, 1970; Pauly and Redisch, 1973), which might alter their ability to respond to economic pressures. In addition, teaching hospitals and hospitals specializing in treatment of severely ill patients presumably have higher costs than other hospital types. Brooks and Jones (1996) show that controlling for merger type is important for explaining why mergers occur and find that mergers between similarly sized hospitals are statistically more likely. It seems plausable that merger type affects the propensity to merge due to the potential cost savings from consolidating with similar or dissimilar types. This paper tests this assumption by analyzing cost savings as a function of the differing characteristics of the merging hospitals.

Alexander *et. al* (1996) attempt to control for differences between merging hospitals. In addition to investigating the entire sample, they also divide the data by whether the merging hospitals are of similar size or similar ownership type. Their results show that the impact of a merger on operating efficiencies is greater when the merger occurs between similarly sized hospitals. In this study, they only distinguish between hospitals of similar or disssimilar type. So, for example, a nonprofit/nonprofit merger is the same as a for-profit/for-profit merger. Given the possible differences in objective functions as discussed above and that studies that indicate differences in technical efficiencies by ownership type (Burgess and Wilson,1996), compressing these two types of mergers into one type may be misleading. Therefore, we separate the merger types to distinguish not only between nonprofit/nonprofit and for-profit/for-profit mergers but also between different merger combinations by hospital size, teaching status, and caseload severity.

Most papers examining hospital costs, including the paper by Connor *et. al* (1998), use a parametric specification. Such models, including the translog cost function, fit the data poorly, and in some circumstances, marginal costs are negative (Vita, 1990). This result should not be surprising given that parametric specifications attempt to fit a particular functional form to the entire set of data. Although in many cases this procedure may be a good approximation to the true underlying function, hospital data are highly skewed due to the presence of small, rural hospitals, and large, teaching hospitals. Thus, an a priori assumption that the cost function will be similar over the entire range of data seems premature.

This paper avoids misspecification by employing nonparametric estimation techniques to estimate expected costs before and after consolidation. The difference between expected costs before and after a merger gives a measure of cost savings from the merger. This paper examines these cost savings to assess whether mergers improve economic efficiency, and then investigates how the merger type, classified by ownership status, teaching status, hospital size and caseload severity affect the cost savings from consolidation.

The next section describes the empirical model used to estimate expected costs and to regress cost savings on characteristics of hospital mergers. Section 3 describes the data and presents summary statistics. Section 4 presents the empirical results and the final section concludes the paper.

2 Model of Hospital Costs

Let C_i represent the costs of hospital i. We then model hospital costs as:

$$C_i = m(\boldsymbol{z_i}) + \epsilon_i, \tag{1}$$

where $\boldsymbol{z_i}$ is a row vector of outputs and other characteristics of the hospital and $E(\epsilon_i \mid \boldsymbol{z}) = 0 \;\; \forall \; i = 1, 2, \ldots, n$. Let the row vector $\boldsymbol{y_i}$ represent the outputs of the hospital while $\boldsymbol{c_i}$ is a row vecctor of the remaining continuous variables. The cost function also includes discrete regressors, defined by a row vector $\boldsymbol{d_i}$, which control for ownership status, teaching status, and location in an urban area. Thus, $\boldsymbol{z_i} = [\boldsymbol{y_i} \quad \boldsymbol{c_i} \quad \boldsymbol{d_i}]$. In addition, let $\boldsymbol{x_i} = [\boldsymbol{y_i} \quad \boldsymbol{c_i}]$ represent the row vector of all continuous variables used to estimate the cost function.

For the continuous regressors, the function, $m(\boldsymbol{x})$, can be approximated locally at a point, $\boldsymbol{x_0}$, by taking a first-order Taylor series expansion such that:

$$m(\boldsymbol{x_0}) \approx m(\boldsymbol{x_0}) + \frac{\partial m(\boldsymbol{x_0})}{\partial \boldsymbol{x}}(\boldsymbol{x} - \boldsymbol{x_0}). \tag{2}$$

Using this expansion and letting $m(\boldsymbol{x_0}) = \alpha(\boldsymbol{x_0})$ and $\frac{\partial m(\boldsymbol{x_0})}{\partial \boldsymbol{x}} = \beta(\boldsymbol{x_0})$, the cost function is estimated by maximizing the following function with respect to α and β:

$$\sum_{i=1}^{n}(C_i - \alpha(\boldsymbol{x_0}) + \beta(\boldsymbol{x_0})(\boldsymbol{x} - \boldsymbol{x_0}))^2 K(\frac{X_i - \boldsymbol{x_0}}{\boldsymbol{H}})L((\boldsymbol{d_i} \mid \boldsymbol{d}, \lambda) \tag{3}$$

where $K(\cdot)$ and $L(\cdot)$ are kernel weighting functions and $\boldsymbol{H}$ and λ are bandwidth parameters for the continuous and discrete regressors respectively.

This estimation technique is referred to as local linear estimation. The more well-known nonparametric Nadarya-Watson estimator is just a special case of the local polynomial estimator where a constant rather than a line is fit to the data so that $\beta(\boldsymbol{x}) = 0$. Rupert and Wand (1994) show that the local linear estimator improves upon the Nadarya-Watson estimator; the local linear estimator has smaller asymptotic bias but the same asymptotic variance when estimating a regression function.[1]

Continuous and discrete regressors require different kernel functions to estimate equation (3). For the continuous regressors, the second-order Gaussian kernel is used and is given by:

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-u^2}{2}\right). \tag{4}$$

Although many other kernel functions exist for continuous data, it can be shown that estimation results are generally not sensitive to the choice of kernel function (see Härdle (1990) or Pagan and Ullah (1999) for further explanation).

For the discrete regressors, we use the kernel method developed by Aitchison and Aitken (1976). Let $\boldsymbol{d_i}$, $\boldsymbol{d} \in \{0,1\}^q$ where q is the number of discrete regressors. Then

$$L(\boldsymbol{d_i} \mid \boldsymbol{d}, \lambda) = (1-\lambda)^{q-\delta(\boldsymbol{d_i},\boldsymbol{d})} \lambda^{\delta(\boldsymbol{d_i},\boldsymbol{d})} \tag{5}$$

where $\delta(\boldsymbol{d_i}, \boldsymbol{d}) = (\boldsymbol{d_i} - \boldsymbol{d})^T(\boldsymbol{d_i} - \boldsymbol{d})$ gives the number of disagreements between $\boldsymbol{d_i}$ and $\boldsymbol{d}$.

The bandwidth parameters are chosen by minimizing

$$\sum_{i=1}^{n} C_i - \widehat{m}_{-i}(\boldsymbol{z}) \tag{6}$$

where $\widehat{m}_{-i}(\boldsymbol{z})$ is obtained in the same manner as $\widehat{m}(\boldsymbol{z})$ with observation i excluded. This method of deriving the bandwidths is computationally intensive. Fortunately, the

[1] See Fan and Gijbels (1996) for further discussion of the properties of local linear estimators.

bandwidth parameters can be expressed as a function of the standard deviation of the regressor, the sample size, and a constant scaling factor which is independent of the sample size. For example, with continuous data, each bandwidth $h_\ell = \psi_\ell \sigma_\ell n^{\frac{-1}{2o+p}}$ where o is the order of the kernel and p gives the number of continuous regressors. Therefore, we use a random subset of the data to obtain ψ_ℓ and then scale up the bandwidths to adjust for the full sample size.

Although all the bandwidth values determine the extent to which the cost function is smoothed, the bandwidths for the discrete regressors have a particular interpretation. Bandwidth values for the discrete regressors can range from 0 to $\frac{1}{2}$ while the continuous regressors can take any non-negative value. As seen from (5), $\lambda = 0$ gives a kernel weight equal to 1 only to hospitals with the same values for all dummy variables. In this case, there is no added benefit to estimating the different categories in the same regression. A value of $\frac{1}{2}$, however, indicates that there is no difference between the categories; including the dummy variables provides no new information to the regression. Thus, values between 0 and $\frac{1}{2}$ indicate the degree to which the categories have common information that can be used in the smoothing process.

Expected costs are calculated for every hospital involved in a merger using the estimates from the cost function. For every merger, let $\widehat{C}_j$ for $j = 1, 2$ be expected costs for the hospitals prior to the merger and $\widehat{C}_k$ be expected costs for the hospital resulting from the merger event. For hospitals j and k, we use expected costs three years prior to the merger and three years following the merger. Expected costs for the merger result are then subtracted from the sum of the hospitals prior to the merger such that:

$$\widehat{CS}_a = \sum_{j=1}^{2} \widehat{C}_{j,t-3} - \widehat{C}_{k,t+3}. \tag{7}$$

where t is the time of the merger event and $\widehat{CS}_a$ gives the actual cost savings from the merger event. If $\widehat{CS}_a$ is positive (negative), cost savings are (not) achieved from the merger of the two hospitals.

In addition to altering costs, the merged hospital may decide to change its output mix, as well as its caseload severity. Such changes may affect the potential cost savings from the merger. For example, assume that $\widehat{CS}_a$ is negative. It is possible that potential cost savings are positive but that the hospital alters its outputs in such as way that it removes all potential efficiency from the merger. An interesting experiment would be to hold outputs and caseload severity constant for the merged entity and calculate whether any potential cost savings exist.

Let $\boldsymbol{y}_{j,t}$ be the actual vector of outputs at time t for each hospital j before the merger. If outputs are held constant for each hospital j after the merger, then the output for the merged entity should be close to $\boldsymbol{y}_{1,t} + \boldsymbol{y}_{2,t} \equiv \widehat{\boldsymbol{y}}_{k,t}$. If economies of scale exist, then the expected costs for the merged entity with this hypothetical output $\widehat{C}(\widehat{\boldsymbol{y}}_{k,t})$ should be lower than the two hospitals functioning independently. For CASEMIX, we average the casemix values for each hospital j such that $\widehat{cmi}_{k,t} = \frac{cmi_{1,t}+cmi_{2,t}}{2}$ represents the hypothetical CASEMIX. We, therefore, calculate $\widehat{C}(\widehat{\boldsymbol{y}}_{k,t}, \widehat{cmi}_{k,t}, \boldsymbol{w}_{k,t})$ (henceforth let

$(\widehat{\boldsymbol{y}}_{k,t}, \widehat{cmi}_{k,t}, \boldsymbol{w}_{k,t}) = (\widehat{\boldsymbol{z}}_{k,t}))$, where $\boldsymbol{w}_{k,t}$ includes all remaining covariates,[2] to obtain:

$$\widehat{CS}_p = \sum_{j=1}^{2} \widehat{C}_{j,t-3} - \widehat{C}(\widehat{\boldsymbol{z}}_{k,t+3}). \tag{8}$$

$\widehat{CS}_p$ gives the potential cost savings from the merger if the output mixture of the two merging hospitals is held constant. $\widehat{CS}_p$ can then be compared to $\widehat{CS}_a$. If $\widehat{CS}_a$ is greater than $\widehat{CS}_p$, then the merging hospitals have altered the output and patient mix to improve on potential cost savings. $\widehat{CS}_a$ less than $\widehat{CS}_p$ indicates that the merged hospitals have failed to realize the economic efficiency gains from the merger.

Let $\boldsymbol{w}$ be a vector of variables with information on the differing characteristics between the merging hospitals. As discussed in Section 2, different types of mergers may affect the potential and actual cost savings from the merger. We investigate this assertion by regressing $\boldsymbol{w}$ on $\widehat{CS}_p$ and $\widehat{CS}_a$ respectively. Estimates from the first regression indicate what type of hospital pairings influence potential cost savings, while the second shows the type of mergers that actually result in cost savings. A positive (negative) sign on a coefficient indicates that cost savings are (not) improved for that particular type of merger pair.

[2] In some cases, hospitals may change their ownership or teaching status due to a merger. In fact, if two hospitals of different ownership status or teaching status merge, the status of one of the hospitals changes in the data. However, given that there is no intuitive way to "add" discrete regressors, the values used for all discrete regressors are the actual values reported by the merged entity after the merger. The definition of TIME remains the same.

3 Description of Data

The primary source of data used in this paper comes from the annual American Hospital Association (AHA) Survey of Hospitals for 1984-1998. With a few exceptions, all information obtained from the survey is self-reported by the hospitals. All United States hospitals, including United States territories, are included in the survey. In those cases where a hospital does not respond to the survey but has not exited the industry, the AHA supplements the survey data with data from other sources and from estimates based on previous information submitted by the hospital. The supplemental data is obtained for key variables such as ownership status, membership in a health care system, number of beds, and number of admissions.

In order to estimate cost functions, information on the expenses of the hospital (EXP), outputs of the hospital (ADMIT, INPAT, OUTPAT), and demographic characteristics of the hospital such as ownership status (FORPROF, NONPROF, GOVT), urban location (URBAN), and teaching status (TEACH) is collected from the AHA Survey. Ellis (1993) raises a valid concern that these variables represent intermediate goods rather than final outputs. However, given the lack of credible data on quality of care and improvement in health after hospital stays, ADMIT, INPAT, and OUTPAT are the conventional measures of output. An index for the wages (WAGE) of every metropolitan statistical area (MSA) and the severity of the caseload for a hospital (CASEMIX) is reported from the Medicare Cost Reports for 1984-1998. WAGE is the traditional measure used in cost functions to account for the prices of inputs. EXP is divided by WAGE to normalize the cost function with respect to labor prices. The number of hospitals for which HCFA computes the CASEMIX is far less than the total number of hospitals reported in the AHA survey for the same year. To overcome this problem, values for CASEMIX are inferred using regression estimates discussed in Appendix A. Although the entire sample of hospitals is used to infer casemix values, we only predict values for hospitals that are denoted in the AHA survey as general and surgical hospitals.

As discussed in the previous section, COST is nonparametrically regressed on the outputs, and characteristics of the hospital, CASEMIX, and TIME to calculate $\widehat{m}(\boldsymbol{x})$. The entire dataset of hospitals, excluding observations with missing data, is used to estimate $\widehat{m}(\boldsymbol{x})$. Table 1 gives the descriptive statistics for all variables used to estimate $\widehat{m}(\boldsymbol{x})$. Any hospital reporting non-acute care classification as an alcohol treatment center, psychiatric hospital, institution for the mentally retarded or rehabilitation facility is deleted from the dataset.

After deleting for missing observations and non-acute care hospitals, $78,615$ observations, from $6,487$ hospitals, remained in the dataset. It is clear from Table 1 that, as discussed earlier, hospital data are highly skewed with a long right tail; the means for COST, ADMIT, OUTPAT, and INPAT are all much higher than the median. Most hospitals are nonprofit, nonteaching hospitals, and located in non-urban areas.

Although all $78,615$ observations are used to estimate the cost function, the function is only evaluated for those hospitals that participated in a merger event, referred to as the evaluation dataset. In particular, this paper studies only mergers that involve two hospitals; mergers with more than two hospitals are deleted from the evaluation dataset. Furthermore, in order to analyze cost savings, we must be able to calculate expected costs for each merging hospital and for the hospital resulting from the merger.

As an example, let hospital A and B merge to form hospital C. If expected costs can be calculated for A and C, but not for B, then the entire merger event is deleted from the dataset.

After accounting for these restrictions, 105 merger events are used in the evaluation dataset, resulting in a total of 310 hospitals and 315 total observations.[3] Table 2 presents the summary statistics for COST, ADMIT, OUTPAT, INPAT, FORPROF, NONPROF, GOVT, TEACH, URBAN, and CASEMIX. Difference of means tests show that, with the exception of FORPROF, GOVT, and URBAN, average values of COST and all other regressors are statistically different (at greater than a 1% level of significance) and larger for the dataset containing only the merged hospitals as compared to the dataset with all hospitals. On average, hospitals that are merging have higher costs than non-merging hospitals. The percentage of for-profit hospitals and hospitals located in urban areas is not statistically different between the two datasets. However, as would be expected, government hospitals are present in the merged dataset at a lower percentage than they are present in the entire dataset.

These 105 merger events form the dataset used to analyze the types of mergers that occur most frequently and how these merger types affect the cost savings of the merger. This paper is particularly interested in investigating differences in i) ownership status, ii) teaching status, iii) hospital size, and iv) severity of caseload for the pair of merging hospitals. Do hospitals tend to merge with another hospital of similar type or do they

[3]In a most cases, two hospitals merge to form a third hospital. In 5 instances, one hospital merges into an existing hospital, rather than forming a new hospital, thus explaining why the total number of hospitals involved is 310 and not 315.

exploit differences in their hospital type in order to achieve greater cost savings?

Hospitals are classified into four separate categories. Ownership status is divided into for-profit, nonprofit, and government hospitals. Hospitals are also divided into teaching and nonteaching hospitals. Quartiles are used to transform the continuous variables, CASEMIX and BEDS, into categorical variables. Using the entire dataset to calculate the quartiles, hospitals with a casemix index higher than the 75th percentile are classified as severe caseload hospitals, while hospitals between the 25th and 75th percentiles, and lower than the 25th percentile are defined as moderate and mild caseload hospitals respectively. The same procedure is performed for BEDS where the categories were big, medium, and small.[4] Table 2a presents the frequencies for CASEMIX and BEDS for the 210 merging hospitals. The hospitals are almost evenly split between severe and moderate caseload hospitals. Medium-sized hospitals are 58% of the evaluation dataset, with large hospitals representing 32% of the sample. Small and mild caseload hospitals represent a small proportion of the merged hospitals.

The different categories of hospital types studied in this paper create a possibility of 6 combinations by ownership status, 3 combinations by teaching status, 6 by hospital size, and 6 by caseload severity. Given these different cells that mergers can fall into, what merger combinations occur most frequently?

Table 3 presents the frequencies for each merger combination. Most mergers occur between two nonprofit hospitals. The remaining merger combinations by ownership type, occur at about the same rate, with the exception of mergers between government

[4] In order to check the validity of this procedure, the densities of CASEMIX and BEDS are investigated. The 25th and 75th percentiles appear to be reasonable points to separate the data.

and for-profit hospitals which never occur. Merger classification by teaching status reveals that teaching hospitals rarely merge with each other. In addition, medium-sized hospitals have a tendency to merge with a hospital of similar size. They also frequently merge with big hospitals. Similarly, hospitals treating severe and moderate cases tend to either merge with the same type or merge with moderate or severe caseloads respectively. Hospitals with mild caseloads have a tendency to merge with moderate caseloads rather than merge with another mild caseload or with a severe caseload hospital.

4 Empirical Results

The first step to investigating cost savings from mergers and the effect of hospital characteristics on these cost savings is to estimate the expected costs for the 310 hospitals involved in the merger event. All nonparametric estimation was performed using the N © program written by Jeff Racine. Table 4 gives the summary statistics for the actual (COST) and expected (ESTCOST) costs of the hospitals. The statistics are quite similar, with a difference of means test failing to reject the null of no difference at greater than a 10 percent level of significance. The bandwidths for the regressors used to estimate the cost function are also presented in Table 5. All of the bandwidths for the discrete regressors are closer to zero than $\frac{1}{2}$, indicating that, although some information is shared between the category types, the types of hospitals are quite different from each other.

The average of expected costs are calculated for: i) each merging hospital three years prior to the merger($\widehat{C}_{j,t-3}\ \forall\, j = 1, 2$), ii) each merger result three years following the merger ($\widehat{C}_{k,t+3}$), and iii) each merger result three years following the merger holding the output mix constant ($\widehat{C}(\hat{\boldsymbol{x}}_{\boldsymbol{k}})$). The difference between i) and ii) ($\widehat{CS}_a$) and i) and iii) ($\widehat{CS}_p$) is then calculated and the descriptive statistics for these potential and actual cost savings are presented in Table 6.

The average potential cost savings from a merger is positive. That is, after controlling for ownership and teaching status, urban location, and time, and assuming that the output mix remains constant after the merger, pre-merger expected costs are larger than the post-merger expected costs of the two merging hospitals. This suggests that, on average, economies of scale and scope can be exploited to reduce costs from their pre-merger values. However, average actual cost savings are also negative, suggesting that, on average, mergers do not result in cost efficiencies. These results indicate that merged hospitals adjust their post-merger outputs to their own detriment; costs increase more than if the output mix had remained constant. Hospitals appear to be pilfering away the economic advantages of merging.

$\widehat{CS}_p$ and $\widehat{CS}_a$ are then regressed on the characteristics of the merger pairs, as shown in Tables 7 and 8. Many specifications were compared to determine the best model. In particular, specifications that use all category types as regressors result in too few observations in each cell and therefore create a small sample problem. Although the categories for caseload defined as severe, moderate, and mild are helpful in examining the frequencies of merger types, classifying mergers under the 6 merger combinations for caseload severity does not help to explain cost savings. Results showed that a continuous variable capturing the difference in the casemix indices between the two merging hospitals, defined as CMIDIFF, improved $\bar{R}^2$. In addition, all merger combinations for ownership status are not necessary for explaining cost savings. All mergers between two nonprofits, two government hospitals, or a nonprofit and a government hospital are grouped together and defined as NFP-NFP. For-profit/for-profit (FP-FP) mergers remain a separate category. All mergers between a for-profit and either a government or nonprofit hospital make up the third category called NFP-FP. We also compress teaching status in a similar manner; mergers between similar teaching types (SAMETEACH) are grouped together. SAMETEACH equals zero when a merger between a teaching and nonteaching hospital occurs. Mergers between big and small hospitals and between medium and small hospitals are also compressed into one category defined as SMALLOTHER. Mergers between two small hospitals are the omitted category. Only the models with the preferred specifications are presented here.

Several merger combinations affect potential cost savings. Mergers between hospitals with similar caseloads increase the potential cost savings from a merger. Results also show that teaching and nonteaching hospitals complement each other to improve post-merger costs. Mergers between two large hospitals, however, are not beneficial for cost savings. If two large hospitals merge, their potential costs after the merger are larger than if the two hospitals had remained separate. As studies such as Wilson and Carey (2001) show, large hospitals exhibit decreasing returns to scale. Thus, it appears that two large hospitals cannot exploit economies of scale when they merge.

Results for actual cost savings report the same qualitative results for a merger between large hospitals; cost savings decrease for such a merger. No other merger characteristics are significant in explaining variations in actual cost savings. Changes in post-merger outputs remove the potential economic advantage from mergers between hospitals with similar caseloads, and teaching and non-teaching hospitals.

For the results presented in Tables 6, 7, and 8, we used hospital data three years prior to and following a merger event (define as $T3$). In order to check robustness of the results, potential and actual cost savings are also calculated for two years prior to and following a merger and also for one year prior to and following a merger (define as $T2$ and $T1$ respectively) . As with the original estimates, we find that, for $T2$, potential and actual cost savings are positive and negative respectively. Regression estimates are also robust when comparing $T2$ and $T3$. However, comparing costs one year before and after a merger shows that potential and actual cost savings are both positive. Further investigation of the data reveals that, on average, costs reported the year immediately following the merger are not representative of the average reported costs for the merged entity in subsequent years. Hospitals are still adjusting to the merger and thus their data do not accurately represent their economic condition. Thus, it is important to account for this transition when investigating the economic gains from mergers.

The bandwidth parameters used to estimate the cost function are also adjusted to check the sensitivity of the results. We find that the results, both for the potential and actual cost savings and for the regressions, are robust to changes in the bandwidths.

5 Conclusion

In this paper, we use nonparametric estimation techniques to examine the potential and actual cost savings from a merger. In addition, merger types are categorized according to the ownership status, teaching status, hospital size and caseload severity of the merging hospitals. These merger types are investigated to determine the types of hospitals that tend to merge with each other and to analyze how differing merger types influence the cost savings from a merger. Our findings suggest that mergers have the potential to save costs, but these cost savings are not realized; costs are higher post-merger than pre-merger. Mergers between teaching and nonteaching hospitals, and hospitals with similar caseloads have the potential to improve cost savings, but the output mix is altered after the merger in such a way that any possible cost savings are eliminated. However, mergers between two large hospitals tend to decrease both potential and actual cost savings.

These results call for additional research analyzing the economic gains from hospital mergers. If cost savings do not improve after a merger, maybe other factors, such as bargaining power with insurance companies, are the dominant reason for mergers. In addition, this study particularly focused on explaining how the characteristics of hospital pairs affect the cost savings from a merger. Presumably, the pairings are affected by the availability of different hospital types in the area. A hospital seeking to merge might prefer another hospital type, but only have the option of merging with another hospital type. This paper admittedly stops short of answering why one hospital chooses to merge with another. Additional studies to better understand the matching process between merging hospitals would give better understanding of this dynamic industry.

Appendix A

Description of Method Used to Predict CASEMIX Values

I regressed observed CASEMIX values on dummy variables that indicate the existence of different types of medical facilities (e.g., cardiac unit, radiology, MRI capabilities) in order to infer CASEMIX values for those hospitals without a HCFA-computed value. Due to missing data, CASEMIX values could not be predicted for all hospitals in any survey year. However, as shown in Table A.1, predicted CASEMIX values were obtained for many hospitals that otherwise would have missing CASEMIX data. The R^2 values were quite high for each regression, ranging from 0.6151 to 0.7599. Table A.2 also shows the encouraging results of the in-sample predictions. For every year that CASEMIX values were reported, 10 percent of hospitals with reported CASEMIX values were randomly drawn and predicted CASEMIX values were obtained using the regression results. For any year, the in-sample predicted values fell between $\pm$ .1 of the actual value at least 60 percent of the time.

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Table 1

Descriptive Statistics of Cost Data

Variables	N	Mean	Median	Standard Deviation	Min	Max
COST	78615	4.27E+07	2.07E+07	6.16E+07	216960	1.03E+09
ADMIT	78615	6045.28	3556	6757.56	4	81492
INPAT	78615	43134.13	24286	52474.89	23	669602
OUTPAT	78615	69386.49	34622	106341.10	0	2350290
CASEMIX	78615	1.19	1.15	0.21	0.43	4.17
FORPROF	78615	0.12	0	0.33	0	1
NONPROF	78615	0.56	1	0.50	0	1
GOVT	78615	0.31	0	0.46	0	1
TEACH	78615	0.07	0	0.26	0	1
URBAN	78615	0.25	0	0.43	0	1

Table 2

Descriptive Statistics of Evaluation Dataset

Variables	N	Mean	Median	Standard Deviation	Min	Max
COST	315	7.33E+07	4.48E+07	8.43E+07	614412.5	5.99E+08
ADMIT	315	8985.05	7062	7167.08	380	38897
INPAT	315	59722.39	49035	47515.21	2011	241869
OUTPAT	315	103723.70	65661	108546.30	2650	712258
CASEMIX	315	1.30	1.24	0.23	0.91	2.11
FORPROF	315	0.12	0	0.33	0	1
NONPROF	315	0.76	1	0.43	0	1
GOVT	315	0.12	0	0.33	0	1
TEACH	315	0.13	0	0.33	0	1
URBAN	315	0.23	0	0.42	0	1

Table 2a

Frequency of CASEMIX and BEDS

Variable	Number of Obs	Frequency	Cumulative Frequency
Big	68	32.38	32.38
Medium	122	58.1	90.48
Small	20	9.52	1.00E+02
Severe	77	36.67	36.67
Moderate	115	54.76	91.43
Small	18	8.57	100

Table 3

Frequency For Each Merger Combination

Variable	Number of Obs	Frequency	Cumulative Frequency
Ownership Status			
Nonprof-Nonprof	67	63.81	63.81
Forprof-Forprof	5	4.76	68.57
Govt-Govt	7	6.67	75.24
Nonprof-Forprof	11	10.48	85.71
Forprof-Govt	5	4.76	90.48
Nonprof-Govt	10	9.52	100
Teaching Status			
Nonteach-Nonteach	85	80.95	80.95
Teach-Teach	3	2.86	83.81
Nonteach-Teach	17	16.19	100
Hospital Size			
Big-Big	16	15.24	15.24
Medium-Medium	42	40	55.24
Small-Small	4	3.81	59.05
Big-Medium	31	29.52	88.57
Big-Small	5	4.76	93.33
Medium-Small	7	6.67	100
Caseload Severity			
Severe-Severe	23	21.9	21.9
Medium-Medium	34	32.38	54.29
Mild-Mild	1	0.95	55.24
Severe-Moderate	31	29.52	84.76
Moderate-Mild	16	15.24	100

Table 4

Descriptive Statistics of Estimated and Actual Costs

Variables	N	Mean	Median	Standard Deviation	Min	Max
COST	315	7.33E+07	4.48E+07	8.43E+07	614413	5.99E+08
ESTCOST	315	7.05E+07	4.23E+07	7.64E+07	91178.4	4.54E+08

Table 5

Bandwidths for Discrete Regressors

Variables	Bandwidths
FORPROF	0.046128
GOVT	0.185522
TEACH	0.223099
URBAN	0.254477

Table 6

Descriptive Statistics of Potential and Actual Cost Savings

Variables	N	Mean	Median	Standard Deviation	Min	Max
$\widehat{CS}_p$	105	4404911	2657512	1.04E+07	-5.89E+07	3.74E+07
$\widehat{CS}_a$	105	-2.36E+07	-1.74E+07	2.54E+07	-1.28E+08	2.15E+07

Table 7

Empirical Results for Potential Cost Savings

Variable	Coefficient	Standard Error	p-value
CONSTANT	3493222	3785818	0.36
FP-FP	3164593	4161372	0.45
NFP-FP	258193	2526153	0.92
SAMETEACH	-5110193	2621309	0.05
BIG-BIG	-9435331	3657369	0.01
MED-MED	2536608	3055734	0.41
BIG-MED	2086472	4372456	0.63
SMALLOTHER	2289868	4922073	0.64
CMIDIFF	2.21E+07	5559932	0.00

Table 8

Empirical Results for Actual Cost Savings

Variable	Coefficient	Standard Error	p-value
CONSTANT	-2.60E+07	9841696	0.01
FP-FP	1.14E+07	1.08E+07	0.30
NFP-FP	-1168134	6567044	0.86
SAMETEACH	9.04E+06	6814411	0.19
BIG-BIG	-2.98E+07	9507777	0.00
MED-MED	460728.3	7943753	0.95
BIG-MED	1.01E+07	1.14E+07	0.38
SMALLOTHER	-2.11E+07	1.28E+07	0.10
CMIDIFF	1.67E+07	1.45E+07	0.25

Table A.1

Results from CASEMIX Predictions

Year	Number of Total Observations	Number of Observations with Reported CASEMIX Values	Number of Observations with Predicted CASEMIX Values	Adjusted R^2
1984	7110	3130	3325	.6151
1985	7102	3131	3317	.6542
1986	7064	3131	3299	.6252
1987	7052	3569	2856	.6581
1988	7037	3513	2983	.6434
1989	6961	3463	2955	.6885
1990	6871	3409	2955	.7185
1991	6829	3367	2945	.7444
1992	6730	3315	2863	.7599
1993	6667	5187	1146	.6921
1994	6591	5100	1047	.6869
1995	6512	5046	1023	.6626
1996	6401	4970	994	.7119
1997	6299	5095	933	.7158
1998	6247	5174	872	.7027

Table A.2

In-Sample Predicted CASEMIX Values Minus Actual CASEMIX Values

Year	Minimum Difference	Maximum Difference	Percentage of Sample Where Difference Less than ± .1
1984	-0.46	0.19	0.93
1985	-0.29	0.20	0.89
1986	-0.43	0.24	0.81
1987	-0.34	0.25	0.78
1988	-0.31	0.38	0.68
1989	-0.36	0.39	0.73
1990	-0.37	0.38	0.70
1991	-0.40	0.26	0.70
1992	-0.58	0.38	0.71
1993	-0.89	0.46	0.64
1994	-0.65	0.48	0.64
1995	-0.75	0.47	0.60
1996	-0.47	0.54	0.60
1997	-0.89	0.59	0.69
1998	-0.60	0.38	0.60